# Leveraging Machine Learning for Fast and Reliable Faulted 3D Modelling

A. Gole[1] and S. Sullivan[2]

1. Machine Learning Engineer, Maptek Pty Ltd, Adelaide SA 5065 arpit.gole@maptek.com.au
2. Technical Lead, Maptek Pty Ltd, Adelaide SA 5065 steve.sullivan@maptek.com.au

## ABSTRACT

Building the best possible 3D model from observed geological data is critical before grade estimation is performed. For many decades, 3D modelling of faults has been a challenging task. Currently, explicit or implicit modelling techniques are widely used to model faults. Explicit modelling is done manually by geologists based on their knowledge and expertise. The reliability of these models depends on the geologists' abilities and creating them is a time-consuming process (Caumon *et al*, 2009; Wellmann and Caumon, 2018). On the other hand, implicit modelling takes a more mathematical approach to describe the fault geometry to combine the fault shape and fault frames (Grose *et al*, 2021; Jessell *et al,* 2014). Godefroy *et al* (2018) introduced kinematics with implicit modelling methods and directly applied them to the implicit description of the faulted surfaces.

It is a challenging task to create 3D geological models comprising faults, as they represent a discontinuity in geological feature(s) that are being modelled. Geological discontinuities and their uncertainties can be easily and consistently modelled using machine learning (Sullivan *et al,* 2019). The underlying architecture of an implicit function has been developed and modified to provide the ability to create geological faulted 3D models in three distinct steps: data preparation; building the fault geometries; and the use of machine learning to generate complex geological faulted 3D models. This approach generates 3D models that fit the supplied data and geological knowledge of the generated fault(s), ie generates a geologically plausible faulted 3D model. The new approach is fast and repeatable compared with existing techniques.

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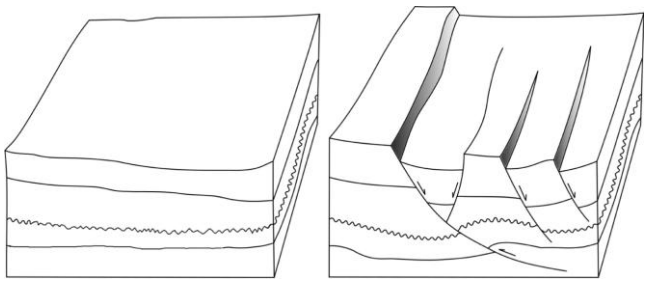
# INTRODUCTION

Constructing 3D models is fundamental in any geological exploration and production phase. A critical aspect of this activity is to take all the various geological factors into account. Faulted 3D model construction is a cumbersome task primarily due to the complexity of the underlying geology, the difference in interpretations of this geology and the occurrence of faults. To ease the modelling of these faults, we propose a machine learning approach. This study aims to make the geologist's decision-making process faster and easier through the fast generation of faulted 3D models that accurately represent geological structures including faults.

There are several challenges in creating faulted 3D models. One of these concerns, uncertainties present in the 3D input data of the underlying geology (Wellmann *et al,* 2010), which may include: (a) inherent randomness, (b) data imprecision or (c) incomplete knowledge. The created 3D model must follow a set of geological criteria to be valid. One example of this is that horizons—the surfaces separating two rock layers—must not intersect themselves (Caumon *et al,* 2009). Generating faulted 3D models that violate these criteria can result in significant issues, such as the reporting of incorrect volumes of geological units. The ability to accurately model faults by capturing the offsets and their impacts on the underlying geology. Ongoing tectonic stresses can create new faults or modify existing ones. In addition, faults do not necessarily need to terminate at other surfaces (Grose *et al,* 2021). Figure 1 illustrates an example of a rock volume and demonstrates how the volume changes in response to deformations caused by faults.



(a) (b)

*FIG 1 – The figure illustrates a rock volume before and after faulting and displacement, adapted from Zhiwei et al (2019). (a) The original rock volume before the fault. (b) The rock volume after faulting, with arrows indicating the direction of movement along the fault plane.*

From a geological point of view, faults develop and can be active over a prolonged period of time. Reactivation of these weaknesses in the Earth's crust is commonplace and often there is negligible evidence of how these faults transformed the subsurface into its present configuration. Therefore, the geologist is responsible for evaluating, based on the evidence available, and inferring how faults have shaped the subsurface. This requires identifying faults within the subsurface rock volume being modelled, using patterns of rock discontinuity observed in geological data, to build an understanding of the chronological order of the original geology.

This study aims to address the various challenges facing geological fault modelling and create a faster and iterative ecosystem for creating faulted 3D models. We introduce a neural network deep learning approach to modelling geology, such as creating the faulted model and specifying the influence of faults on one another and the rock layers. We also model how faults cut through the rock layers and take chronological precedence over other fault(s).

## METHODOLOGY

The method builds on the existing DomainMCF application, a machine learning approach developed by Maptek (Sullivan *et al,* 2019). It uses raw drill hole data as input to improve the orebody modelling process and capture the spatial continuity in the geological data. DomainMCF builds an artificial neural network (ANN) model to understand the spatial distribution of discrete domain values from a set of samples.

ANNs, such as those developed and deployed in DomainMCF, typically have an architecture as shown in Figure 2. The ANN consists of multiple layers of processing elements (PEs) also known as neurons (McCulloch and Pitts, 1943). There are three types of layers and corresponding PEs—input, hidden and output. PEs from one layer are connected to PEs in the next layer using weighted links known as synapses. PEs transfer the input signal to their outputs using an activation function that differs between the three types of layers.

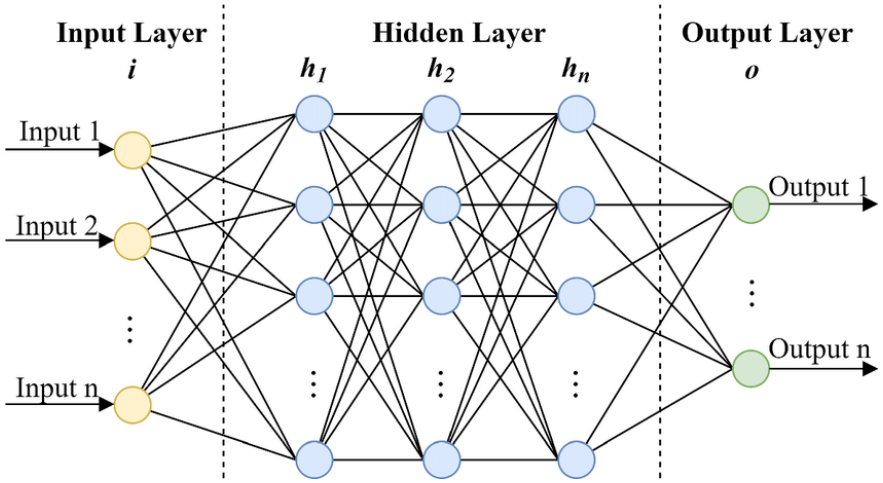



*FIG 2 – Lisheen mine data drill hole sample locations with the study area highlighted.*

In case of DomainMCF, the architecture of the neural network is dynamically decided based on the input data and the fault structure(s) provided by the user, ie the number of hidden layers and PEs per hidden layer are controlled by a process that will find the best configuration based on the user data. For any given sample, the x, y, z coordinates and the information about the fault structure(s) are used as the input to DomainMCF's ANN. Then the ANN is trained to predict the sample domain(s) and, optionally, sample grade(s) and other numeric attributes as the required output. During the inference step, for any given sample location x, y, z and the information about the fault structure(s) provided as an input. As the fault information changes depending on the query location, the predictions obtained for domain and grade are influenced by the faults.

The quality of the ANN trained is directly related to the quality and the quantity of the drilling data supplied to DomainMCF. It is generally accepted that when building a complex 3D model for grade estimation or resource estimation, more samples will be required to train a complex ANN architecture with more PEs and hidden layers, which is essential to capture a geologically complex scenario.

Once the data is supplied and the ANN is trained to understand the quality of the trained model, the following metrics are used:

For categorical variables, the evaluation metric is the accuracy:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

where *TP* is the number of *true positive* predictions, *TN* is the number of *true negative* predictions, *FP* is the number of *false positive* predictions, and *FN* is the number of false negative predictions.

For numerical variables, the root mean squared error (RMSE) is used:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N} (Predicted_i - Actual_i)^2}{N}}$$

## CASE HISTORY

The following case studies demonstrate the application of the study method and compare the results.

The Lisheen mine in County Tipperary, Ireland, was mined from 1999 until the mine closure in December 2015. It produced 22 Mt at 11.6 per cent Zn and 1.9 per cent Pb (Torremans *et al,* 2018). Mineralisation at Lisheen consists of several, largely stratiform, massive sulfide orebodies at or within 30 m of Lower Carboniferous marine carbonates and breccias. The mineralisation is manifest by semi-massive, disseminated, and vein-hosted sulfides in a complex of laterally discontinuous normal faults (Hitzman, 1999).

Bonson, Walsh and Carboni (2012) presented results from studies of the structural geology of three mines in the Lisheen field, which supported a model invoking the existence of normal fault boundaries to be responsible for the localisation of up-fault fluid flow of metal bearing fluids and their entrapment within stratiform dolomite breccias. Normal faults which host these Zn-Pb deposits are generally highly segmented, north-dipping normal faults that offset the Lower Carboniferous succession on the order of 200–400 m. Fault segments tend to strike E-W or ENE-WSW and are arranged in NE-SW oriented, left-stepping, *en échelon* arrays.

A comprehensive 3D synthesis of the base metal mines in Ireland was published by Kyne *et al* (2019). Their research used a combination of traditional section interpretation, wireframing and fault interpolation to define geometric and kinematic links between faulting, structure and mineralisation as shown in Figure 3.

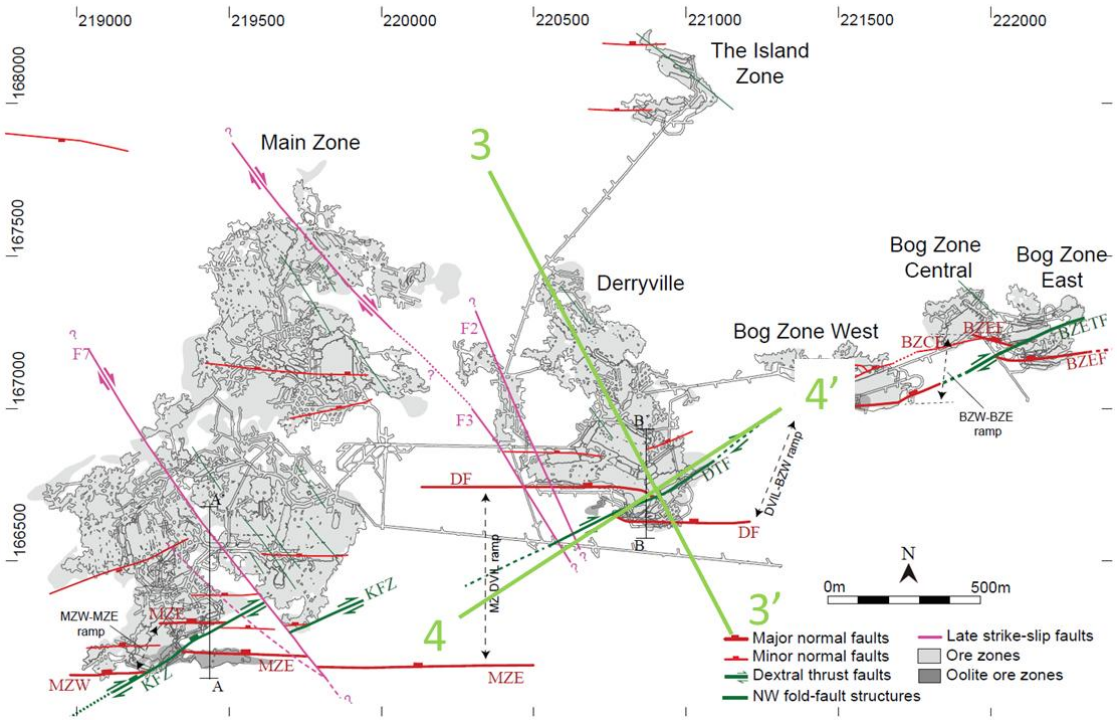



*FIG 3 – Structural setting of the Lisheen base metal deposits in Ireland (from Kyne et al, 2019 modified from Torremans et al, 2018).*

## Previous geological modelling

The Lisheen deposits contain over 7000 published holes, drilled from the surface during exploration and subsequently from underground during mine production. Holes were geologically logged with more than 40 different domain codes being used to describe the host rocks and mineralised intervals. Chemical analysis of mineralised intervals and surrounding host rocks includes determinations for Zn, Pb and a wide suite of related elements.

Modelling during the operation of the Lisheen mines used sectional interpretation of exploration and production drilling and underground channel sampling/mapping observations. Explicit wireframes were created for the footwall and hanging wall of each mineralised horizon. These two surfaces were then combined to make a solid model of each horizon, which was then used to flag an ore code into a 3D block model.

The mine geologists at Lisheen would update their resource model on a 6 or 12-month cycle. Interpretation and correlation between drill holes on a sectional basis and update of wireframes was a manual process that would take at least a week (Colin Badenhorst, personal communication). The comprehensive 3D modelling and structural synthesis by Kyne *et al* (2019), did not document the time involved in building their models. A plan view from their work is shown in Figure 4.

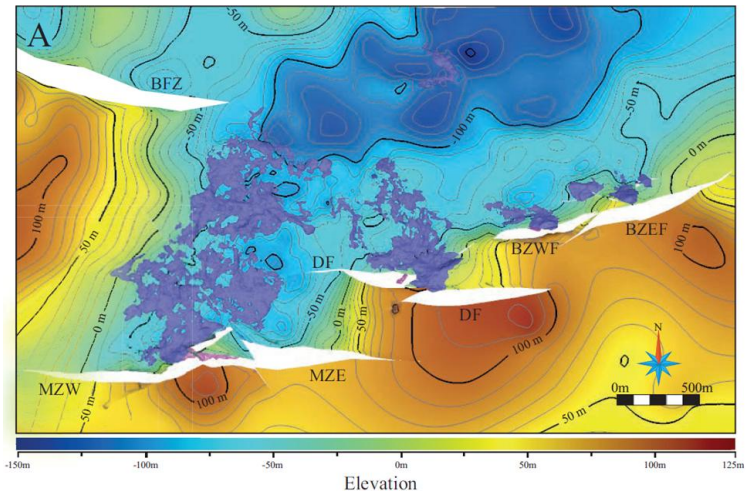



*FIG 4 – Plan view of the 3D model generated by Kyne et al (2019). The white E-W trending shapes are interpreted faults and are equivalent to the faults marked and annotated in red in Figure 3. The contours represent the elevation above sea level.*

## Modelling using Machine Learning

The rapid advance of computing power facilitates computer-based discovery and analysis. In the geological context, this allows us to generate a documented workflow which updates the model when the input data changes. This could be a manual process but the most benefit is derived from an automated system which is triggered by a change in state in the underlying data.

This current study built a 3D geological model using the latest commercial machine learning engine, DomainMCF. The details of the data preparation, data validation and the results of the geological modelling process for one of the Lisheen deposits using machine learning are presented in Sullivan (2022). The DomainMCF system processes the input geological data using multi-threaded cloud computing with cyber secure data transfer for data upload and model download.

Before data is uploaded, it needs to be validated. There are hosts of simple rules that can be applied in this process: checking the validity of collar x, y, and z coordinates; checking *from and to* sample intervals are not missing or overlapping; and checking that analytical data uses the same units of measurement. Data validation rules are built into DomainMCF so that data going through the modelling process is as clean as required. This process is critical as erroneous input data will directly impact the output models.

The machine learning process analyses local and surrounding data, taking into account the orientation, width and other characteristics, and automatically works out where two intervals are not continuous and have been displaced. No manual intervention is required, unlike with grid-based and implicit modelling that wraps a continuous surface between geological data intersections.

Upon generation of any model, it is important to compare it with the input data. For domain codes, this is most easily accomplished by viewing cross-sections in two perpendicular orientations and also in plan view. Data-driven modelling can be brutal as it will honour intervals of inliers and outliers in the data, which otherwise would be glossed or smoothed over during manual interpretation.

Modelled fault breaks are easily visualised using your preferred three-dimensional viewing software. The results of the machine learning process correlate well with interpreted fault models built and observations made during underground mining and mapping at Lisheen as shown in the Figure 5.

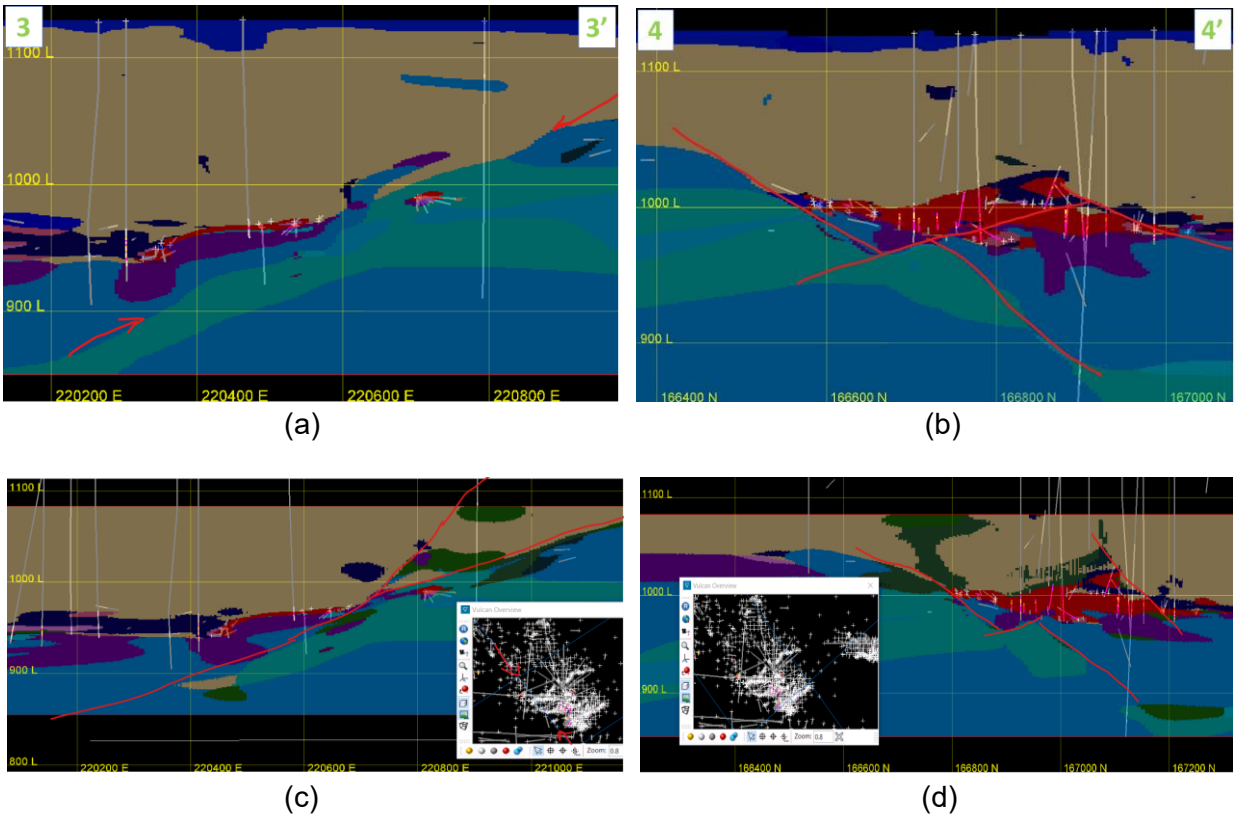



*FIG 5 – Cross-sections showing displacement of mineralisation (red domain) across the Derryville thrust. (a) Cross-section 3–3' looking NE (as located on Figure 3) showing displacement of mineralisation (red domain) across the Derryville dextral thrust; (b) Cross-section 4–4' (as located on Figure 3) looking NW showing displacement across the Derryville (north dipping) complicated by interaction with the Derryville south dipping thrust; (c) Cross-section along strike from section 3–3' looking NE (as located on Figure 3) showing displacement of mineralisation (red domain) across the Derryville dextral thrust; (d) Cross-section parallel to section 4–4' (as located on Figure 3) looking NW showing displacement across the Derryville (north dipping) complicated by interaction with the Derryville south-dipping thrust.*

A comprehensive review across all sections and plans shows that the DomainMCF data-driven model honours the mineralised data, its surrounding host rocks and displacements along faults, better and faster than the manual interpretation and consequent wireframe models. Empirically, the result of the domain prediction resulted in an overall accuracy of 84.9 per cent. We can right away see that immediate value is gained in the modelling process by using the machine learning approach which is fast and reliable for generating faulted 3D models.

## CONCLUSION AND FUTURE WORK

The Lisheen mine data has been subjected to a data-driven modelling process and the resultant models appear superior in mapping the input data compared with a manually controlled process. The correlation between drill data has been derived purely from the input data without bias from the operator. Spatial correlation of domains during the machine learning process has another advantage of adopting the data-driven modelling approach at Lisheen is the speed at which results are generated. The modelling of all mineralised and host rock domains from the raw input data occurred in less than 30 mins. As this is now an automated process, as new data is collected, a model update can be triggered by a change in the data state and the model can always be up to date, no matter the speed or frequency of data collection.

Thus machine learning gives geologists more time to analyse results, change settings and run multiple iterations to refine outputs to provide the best possible model(s).

Data-driven geological modelling has not yet been adopted by mainstream mine and resource geologists but as the benefits of its use become widespread, we will look back and wonder why it took so long to embed into our daily processes. Machine learning is not just for traditional mines, as shown in Kapageridis *et al* (2021), which discussed the application of machine learning for domain classification in the quarrying environment. The new approach will become ubiquitous in our world, just as mobile phones and the internet have changed the way we work.

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